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ABSTRACT

Since the 1980s Artificial Neural Networks (ANNs) have experienced a dramatic resurgence and have been applied to a broad range of different problems, mainly in engineering, medicine, finance and management. They have also become increasingly common in Nuclear Fusion, where the most interesting results have been obtained in the fields of signal processing, real time control and data analysis, where they can compete successfully or complement effectively traditional algorithmic approaches. With regard to signal processing, ANNs can be very useful in modelling non-linear transfer functions and solving ill-posed problems, in various forms of pattern recognition and identification. They have indeed been applied successfully in deriving global information from tomographic diagnostics and in identifying spectral lines for erosion monitoring. So far ANNs have probably found the most common applications in real time control, for their speed and generalisation capabilities. The identification of locked mode position and the estimate of the magnetic axis location are some examples in which their potentials have been decisive in obtaining good results within the required time. In the field of real time ANNs can also been used to complement algorithmic approaches, like the evaluation of the internal inductance estimated from the external magnetic measurements. As far as data analysis is concerned, ANNs can be particularly efficient in automatically extracting diffuse information from complex data, reducing the need of time consuming human supervision. A typical example is the derivation of relevant physical quantities from Langmuir probes. They can also be very useful in identifying the relevant parameters in complicated physical problems, implementing various forms of correlation techniques. The positive results obtained so far motivate the study of more complex architectures and the implementation of advanced concepts like fuzzy logic and adaptive control.

1 INTRODUCTION

The development of Artificial Neural Networks (ANNs) was historically motivated by the interest in modelling the behaviour of the neurons in the human brain, but already one among the first publications in the field [1] dealt with important computational aspects. In particular the two authors, Warren McCulloch and Walter Pitts, managed to prove the equivalence of ANNs to a Turing machine and showed that simple networks could learn. By the end of the 1960s, the basic concepts for neural computing had already been formulated but this approach was not really pursued until the 1980s. This delay was due both to technological difficulties, unavailability of workstations powerful enough, and to pessimistic theoretical results. In particular the Minsky and Papert work [2] on the limitation of one layer perceptrons had a very discouraging impact on the Artificial Intelligence (AI) community. In the 1980s the availability of PCs increased dramatically the interest in ANNs and the theoretical resurgence of activity culminated with the backpropagation learning algorithm, first introduced by Bryson and Ho [3] in 1969. In those years it became clear not only that multilayer ANNs could model non-linear functions but also that a sound learning procedure was available.

Since the 1980s the development and progress in ANNs has constantly increased and has recently entered even the field of Nuclear Fusion research. The ANN potential to implement non-linear transfer functions is very important in a domain characterised by complex and strong non-linear problems. In this respect, a useful application consists of the fast estimate of the total radiated power, without making recourse to demanding tomographic reconstructions. In JET two ANNs have been trained and tested to provide the total radiated power and the divertor emission with an accuracy clearly better than the linear combination of chords [4], which is often a bit simplistically implemented in many machines. In the determination of the internal plasma inductance based on the Shafranov integrals, ANNs can also be successfully applied to determine this volume dependent parameter [5], difficult to derive from the external magnetic measurements, which allow only the proper determination of the fields at the last closed magnetic surface.

Up to now ANNs have probably found the most useful applications in the real time identification of several plasma parameters. Indeed the real time control of the configuration is certainly one of the crucial topic of JET and of the international research program toward a reactor. In this contest, ANNs offer clear advantages in terms of speed and generalisation capabilities. They have already been successfully used to identify the locked mode position in the Reversed Field Pinch RFX [6], whereas in JET this approach is carefully considered to achieve a fast identification of the magnetic axis position [5].

For monitoring and general surveying, ANNs can also present several advantages and can help reducing the presence of the human operator. In the contest of the erosion studies, we have already developed an ANN to recognise the lines emitted by high atomic number materials, like tungsten (W) and hafnium (Hf). These transition metals could be used as markers in the tiles and provide information about the global plasma wall interactions in a next step experiment like ITER.
Finally, with regard to data analysis, in RFX ANNs have been used to derive a relevant physical quantity, the electronic temperature at the plasma edge, from the raw measurements of the Langmuir probes [7].

With regard to the paper structure, next section is devoted to a general description of the ANN architectural characteristics more relevant to the applications described in this paper. In section 3, the advantage of feedforward networks in modelling non-linear transfer functions are emphasised, whereas in the following section several examples illustrate the potential of ANNs in the field of real time control and identification. Some applications of neural networks in the field of global monitoring of plasmas, with the aim of reducing the human supervision, are reported in section 5, whereas the use of this software tool in data analysis, to retrieve diffuse and problematic information, is described in the following section. The prospects of future and more advanced networks are briefly discussed in the last section of the paper.

2. GENERAL DESCRIPTION OF THE ARTIFICIAL NEURAL NETWORKS USED IN THE FOLLOWING APPLICATIONS

The general architecture of the adopted ANNs consists of a feedforward multi-layer perceptron

(MLP) with a single hidden layer, i.e. the ANNs are made of three layers: an input layer, an hidden layer and an output layer; each unit of a layer is connected, by means of weights connections, to every unit of the previous and/or the following layer. A typical MLP scheme is shown in fig. 1.

The relation that links the outputs y_k to the inputs x_i is given by

$$y_k = \hat{g}\left(\sum_{j=0}^{m} \hat{w}_{kj} \cdot g\left(\sum_{i=0}^{d} w_{ji}\, x_i\right)\right) \tag{1}$$

where g is a non-linear activation function (the hyperbolic tangent), $\hat{g}$ a linear one and the w's are the weights. It can be indeed demonstrated that at least in principle every continuous function can be reproduced by a feedforward ANN with a single hidden layer, for a finite range of the input values, and that, being g a non-linear activation function, an ANN has the ability of modelling in principle arbitrary transfer functions [8].

Since the ANNs are supervised, they have been trained using the error backpropagation method. In particular, the ANNs for the determination of the JET radiated power, the RFX electronic temperature and the RFX locked mode position adopt the gradient descent rule, while the ANNs used in the determination of the JET internal inductance and magnetic axis position, and in the context of the erosion materials, involve the Levenberg-Marquardt rule [8]. The error function is the following, which is proportional to the mean squared error:

$$E = \frac{1}{2} \sum_{k=1}^{c} (y_k - t_k)^2 \tag{2}$$

(where t_k is the k^{th} desired output). Though used in most applications, expression (2) does not represent the unique error function adopted in practice. In fact any error function whose derivative can be calculated at the output layer may be used instead, taking into account possible relations among the activation values of the output units. For example, an alternative error function has been considered in the computation of the electronic temperature from Langmuir probes data samples [7], based on the exponential shape of the function to be reproduced (see section 6).

3. APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS AS NON-LINEAR TRANSFER FUNCTIONS

As mentioned in the previous section, if a non-linear activation function is chosen, ANNs can reproduce effectively non-linear transfer functions. This property can be exploited with great advantage in Nuclear Fusion, where many quantities depend non-linearly on several parameters. A typical example is the rapid calculation of the total and the divertor radiated powers. These quantities are normally obtained from complicated tomographic inversions of bolometric diagnostics, which provide line integrated measurements of the emitted radiation. The inversion of these integral quantities, to derive the local plasma emission, is a matemathically ill-posed problem, which results therefore very demanding in terms both of expertise and computational time. Historically, it has therefore become a standard procedure to approximately calculate the total power using suitable linear combinations of the line-integrated measurements. This is not always a satisfactory approach, since in many machines the tomographic reconstructions are indeed non-linear operators because they have to include special regularisation and constraints. In these cases, a non-linear transfer function can provide a better approximation of the required power. This has been demonstrated in JET, where two dedicated ANNs have been trained to provide respectively the total radiated power and the power emitted from the divertor [4].

The comparison between the ANN and the linear operator estimate of the total power, using the proper tomographic inversion of the bolometric data as a reference, is reported in fig. 2 for a typical JET shot. The results of a statistical comparison between the ANN and linear operator approaches, with respect to the tomographic reconstruction, for a database of 30 shots (the test set), are summarised in table I, where the results related also to the divertor power ANN has been reported. The better agreement of the ANN with tomography is clear and becomes particularly evident for emission profiles particularly different from the usual, confirming the good generalisation capabilities of ANNs. Moreover, the ANN outputs can also follow the trend of the power during ELMs, and this is an additional feature that tomography reconstructions normally do not have (because the computational resources required for such a time intensive analysis would be prohibitive). Finally, it has also to be mentioned that the maintenance of ANNs is normally easier compared to traditional algorithms. If any change is to be implemented, the retraining of the network is relatively easy, whereas the algorithmic solutions require strong involvement of the experts to be carried out.

A similar problem is faced when trying to determine the plasma internal inductance l_i using the external magnetic coils. Even in this case this global quantity, which depends on the details of the current distribution, must be determined from external measurements. The internal inductance has been shown to depend on the three Shafranov integrals, S_1, S_2 and S_3, the elongation k, the second Shafranov moment Y_2, the Shafranov shift δ and an additional parameter α_s (which by itself requires the knowledge of the poloidal magnetic field on the plasma boundary) [5].

Even if the plasma internal inductance can be expressed as a linear combination of the aforementioned parameters, anyway this estimate is an approximation, and therefore a specific ANN has been trained in JET in order to try to reproduce the underlying transfer function. For this purpose, a database of about 6000 patterns has been chosen to cover an ample variety of JET discharges. The inputs to the ANN are the same as the algorithmic approach.

The evolution of an ANN l_i estimate during a pulse is shown in fig. 3, together with an estimate supplied by the current real time algorithm used to determine the internal inductance [5] and an estimate by the offline code EFIT [9]. A statistical comparison between the results of the algorithmic method and the ANN approach for the real-time evaluation of l_i is reported in table II. In this case the database is made of about 1400 patterns not used for the training of the ANN. MRE[1] and MSE[2] are respectively the Mean Relative Error and the Mean Squared Error with respect to EFIT.

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[1] $MRE = \left(\sum_{i=1}^{N} \left\| \frac{(S_i^R - S_i^B)}{S_i^R} \right\| \right) / N,$ where S^R is the reference off-line signal, S^B is the analogous real time signal from the alogrithmic method or the ANN, and N is the total number os samples

[2] $MSE = \left(\sum_{i=1}^{N} (S_i^R - S_i^B)^2 \right) / N$

4. REAL TIME APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS FOR CONTROL AND IDENTIFICATION

To implement fast real time control schemes, ANNs present the potential of being simple transfer functions, whose outputs can therefore be calculated on a sub-millisecond time scale. This can become a fundamental advantage when computational time is a crucial issue. One example of this type of problem is the determination of the locked mode position in a magnetic configuration characterised by a fast dynamic of the magnetic fields. The location of this magnetic deformation is obtained from the magnetic pick-up coils, involving sophisticated Fourier expansions to derive the spatial information required. In a machine like RFX, characterised by very short time scales, inferior to 1 ms, the algorithms, even if they are linear, result too complicated to be computed in real time. Therefore a specific ANN has been trained to determine the position of the locked mode, which is characterised by a concentrated localised helical deformation of the plasma column. This deformation, which can be static or can rotate in the laboratory reference frame, is due to the locking in phase of the MHD resonant tearing modes with characteristic spectra $m = 1$ and $n = 7\text{-}12$ (where m represents the poloidal Fourier expansion around the torus and n the toroidal one) [6].

In fig. 4 the temporal evolution of the toroidal odd magnetic field for Pulse No:12336 is shown: this quantity is directly related to the position of the locked mode, as it can be seen comparing fig. 4 to fig. 5. Indeed fig. 5 shows the estimates of the spatial evolution of the locked mode position as computed by an offline Fourier series expansion (dashed line) and by the ANN (solid line). The toroidal sectors (each of which has an extension of 30^{o}) are related to the position of the toroidal coils, which are supposed to be used to rotate the helical deformation, and correspond to increasing values of the toroidal coordinate.

The performance of this ANN, with respect to the offline algorithm, is reported in table III. P_{15} indicates the percentage of cases in which the ANN computes an angular position with an error less than the extension of a toroidal coil sector, whereas P_{30} indicates the percentage of cases in which the error is within one adjacent toroidal coil sector.

Always in the real time field, a specific ANN has been also developed in JET to determine the magnetic axis radial position R_{MAG}, a quantity that is currently computed in real time by an algorithm, but with an approximate expression [5]. The evaluation of this plasma parameter is a particularly delicate subject, due to the lack of direct measurements and the complicated dependence of this quantity on various aspects of the magnetic configuration. This challenging task constitutes a further prove of the ANN effectiveness in attacking poorly understood and diagnosed issues with a limited amount of resources.

The chosen inputs to the ANN for the evaluation of R_{MAG} are the same as the algorithmic approach, i.e. the Shafranov integrals S_1 and S_2, the plasma major and minor radii R_0 and a, and the Shafranov shift δ, while the database is the same as the internal inductance ANN. The evolution of an ANN R_{MAG} estimate during a pulse is shown in fig. 6, together with an estimate supplied by the current real time algorithm and an estimate by the offline code EFIT. A statistical comparison between the results of the algorithmic method and the ANN approach for the real-time evaluation of R_{MAG} is reported in table IV; also in this case the database is the same as the l_i statistical comparison.

5. REAL TIME APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS FOR GENERAL SURVEYING OF PLASMAS

Always in the context of real time applications, ANNs can also become very useful to reduce the burden of the human operators in the case of general surveying. In Next Step Experiments, for example, it is very likely that the first wall erosion will be a major issue, requiring very close monitoring. Therefore in JET a dedicated program is focused on studying the possibility to deposit suitable materials (belonging to the transition elements and therefore with high atomic number Z) into the tiles and detect spectroscopically when the erosion has reached these implants [10]. Once into the main plasma these high Z transition metals emit characteristic lines, which have to be identified to assess how deeply the first wall is being eroded.

A dedicated ANN has been designed and trained by us to recognise the spectroscopic fingerprint of the various materials once they are emitting from the main plasma. An example of the spectra in question is reported in fig. 7 for W, Hf and composite W/Hf targets. The training set has been designed first determining the best wavelength interval, where the spectra present the most different features with respect to each other, and then excluding some spectra, in particular those belonging to the pre-ablation phase and the saturated ones.

In this preliminary phase of study, the adopted ANN has been able to classify successfully all the 25 data patterns, related to the different markers, of the test set (a third of the overall data set). For the future it has been foreseen to include in the data set also spectra from other transition metals, like zirconium, molybdenum and nickel, to prove the versatility of the approach.

6. ARTIFICIAL NEURAL NETWORKS IN THE FIELD OF DATA ANALYSIS

In the field of data analysis, ANNs can become useful when it is difficult to retrieve the required information because it is immersed in noisy or diffuse data. When these issues are addressed with traditional algorithmic approaches, the solutions normally imply a substantial amount of computational efforts. This difficulty can often be at least partially alleviated by the use of ANNs. As an example, we describe a dedicated ANN developed in RFX to speed up the intershot analysis of data acquired by Langmuir probes and used to determine the electronic temperature at the plasma edge [7]. Indeed the calculation of the temperature, with the usual fitting procedures, requires a lot of computational time as well as the human supervision.

In this case each input pattern consists of a noisy exponential characteristic (the current flowing on a probe in a certain time window), and the number of outputs is equal to the number of inputs (40 points) plus one: the ANN is able to reproduce the filtered version of the exponential in the outputs from 1 to 40, and to determine the slope of the exponential (which is inversely proportional to the temperature) in output 0. Indeed this has been possible adopting the following error function:

$$E = \frac{1}{2} \sum_{k=1}^{c} (y_k - t_k)^2 + \frac{1}{2} \sum_{k=1}^{c} (y_k\, y_0 - t_k\, t_0)^2 \qquad (3)$$

The rationale behind this error function is due to the exponential shape of the function to be reproduced. It turns out that the second term of (3) involves the derivative of the exponential curve, carrying therefore the information on the temperature.

In fig. 8 there is an example of a filtered version of an exponential curve, as computed by the ANN, superimposed to the related noisy input pattern. Instead fig. 9 shows an example of comparison of estimates of electronic temperature at the plasma edge as computed by the ANN and by the fitting procedure, during an RFX pulse. Considering that the intrinsic error in the evaluation of the electronic temperature with the fitting procedure is estimated as being between 20% and 30%, it can be stated that there is acceptable accordance between the two methods.

7. FUTURE PROSPECTS AND THE USE OF MORE SOPHISTICATED ARTIFICIAL NEURAL NETWORKS

The use of ANNs in various fields of nuclear fusion, ranging from real time and surveying applications to data analysis and modelling of non-linear transfer functions, can be considered generally very positive. The networks normally present better accuracy than the usual algorithmic approaches, require less computational time and can very often be upgraded with less manpower. These positive aspects have motivated the developments of more ambitious applications, among which one of the most interesting is the possibility to use networks to study and try to predict and classify disruptions [11,12,13]. Also the systematic use of ANNs in complicated multivariable feedback loops, like the ones used in the control of the safety factor profile, are being investigated. Even if it is premature to draw a conclusion about the results of these attempts, it would be astonishing if appropriate networks, having performed very well so far, would not be able to give a positive contribution even in addressing more difficult issues.

One of the fields in which ANNs could have a significant impact is certainly the one of feedback control. In addition to the obvious advantage of potentially reducing the computational time, ANNs could probably be useful in handling highly non-linear phenomena. The real time control of the transport barriers, for example, could strongly benefit from the application of soft computational tools like ANNs. The combination of neural networks with fuzzy logic approaches could also have a very positive impact in a field like nuclear fusion, characterised by non-linear interactions of a high number of often poorly controlled variables.

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Power estimates	Lin. op. 10%	Lin. op. 20%	ANN 10%	ANN 20%
Total power	68	89	83	91
Divertor power	22	44	70	89

Table I: Statistical comparison between the ANN and linear operator estimates of the total and radiated power, with respect to the tomographic reconstruction. The percentages of the estimates, which fall in the ±10% and ±20% intervals, centred around the tomographic reconstruction calculation, are shown.

Internal inductance calculation method	MRE (%)	MSE
ANN	1.54	0.00059
algorithm	2.84	0.0013

Table II: Statistical comparison between the ANN and algorithmic estimates of the internal inductance. MRE and MSE are the Mean Relative Error and the Mean Squared error with respect to the offline code EFIT computed on a database of about 1400 patterns.

Type of percentage	Performance (%)
$\mathbf{P_{15}}$	67
$\mathbf{P_{30}}$	90

Table III: Performance of the ANN for the determination of the locked mode position with respect to the offline algorithm. P_{15} indicates the percentage of cases in which the ANN computes an angular position with an error less than the extension of a toroidal coil sector, while P_{30} indicates the percentage of cases in which the error is within one adjacent toroidal coil sector.

Magn. axis position calculation method	MRE (%)	MSE
ANN	0.073	$1e^{-5}$
algorithm	0.33	$1.2e^{-4}$

Table IV: Statistical comparison between the ANN and algorithmic estimates of the magnetic axis radial position. MRE and MSE are computed with respect to the offline code EFIT on a database of about 1400 patterns.

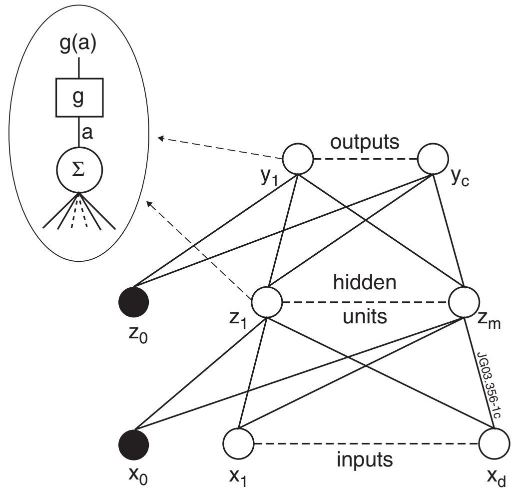

Figure 1: Pictorial view of a feedforward multi-layer perceptron.

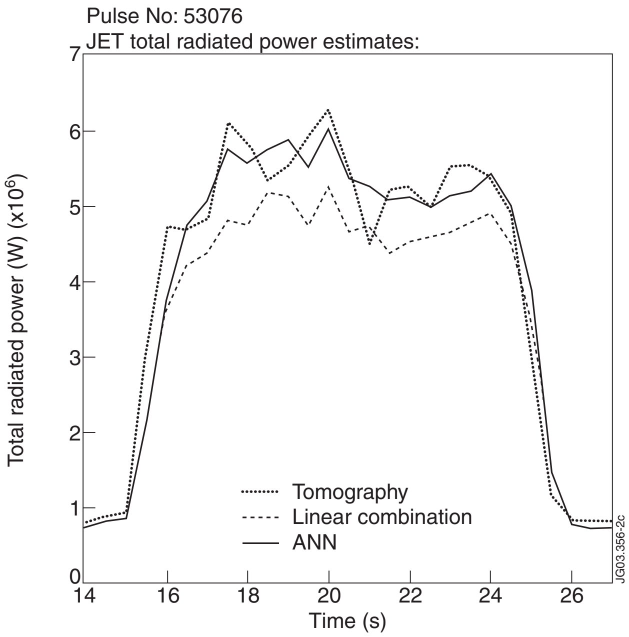

Figure 2: Comparison of the JET total radiated power as computed by the ANN (bold solid line), linear combination (thin solid line) and tomographic inversion (dashed line) approaches for Pulse No: 53076.

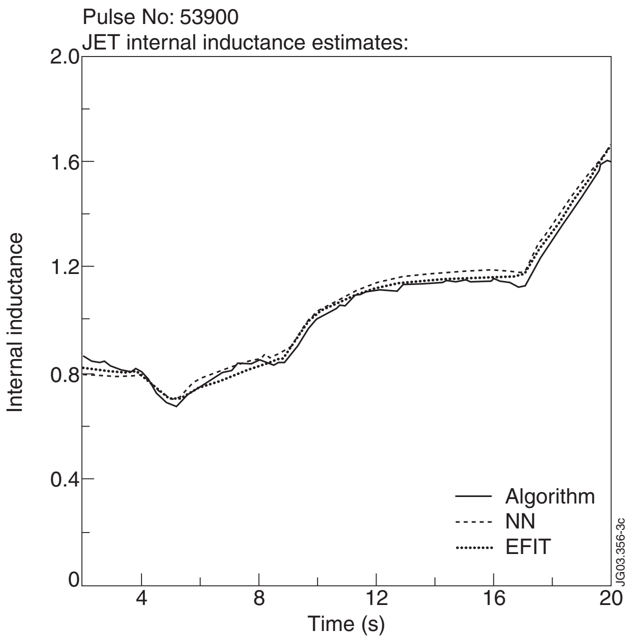

Figure 3: Comparison of the JET internal inductance as computed by the ANN (dotted line), the real time algorithm (thin solid line) and EFIT (bold solid line) approaches for Pulse No: 53900.

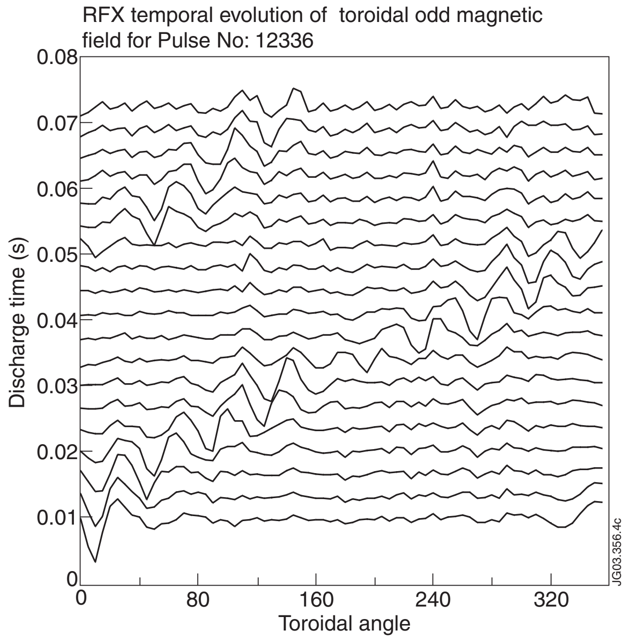

Figure 4: Temporal evolution of the RFX toroidal odd magnetic field for Pulse No: 12336.

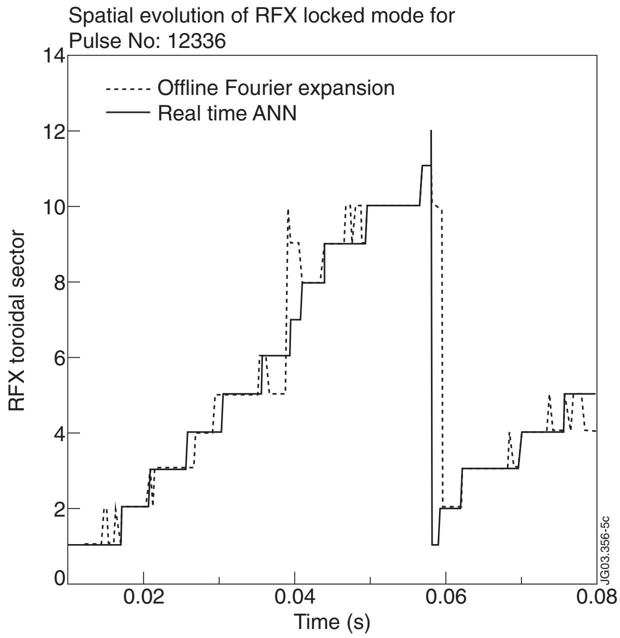

Figure 5: Spatial evolution of the RFX locked mode for Pulse No: 12336: comparison between the offline Fourier series expansion (dashed line) and the ANN (solid line) estimates.

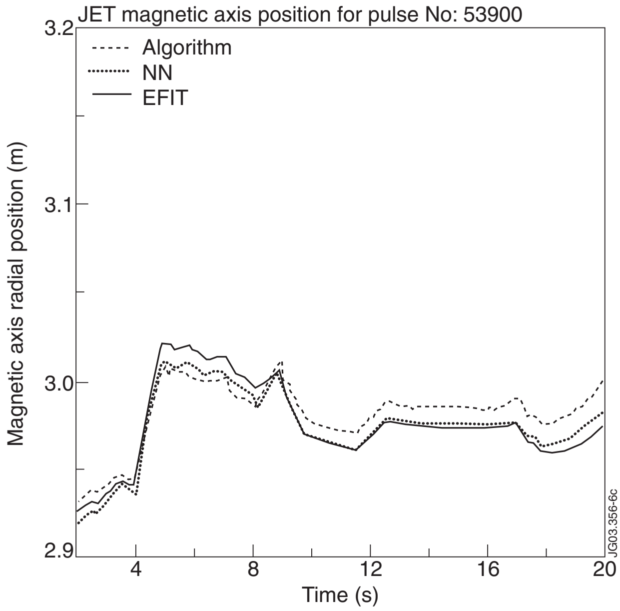

Figure 6: Comparison of the JET magnetic axis radial position as computed by the ANN (dotted line), the real time algorithm (thin solid line) and EFIT (bold solid line) approaches for Pulse No: 53900.

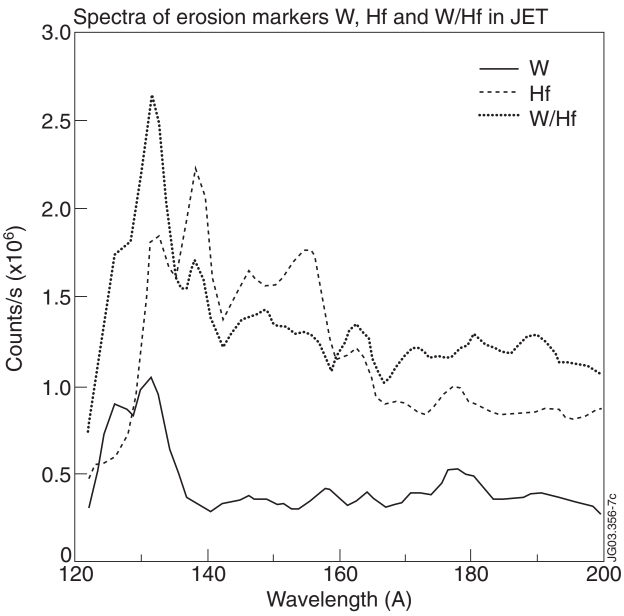

Figure 7: Example of the spectra of W (tungsten), Hf (Hafnium) and composite W/Hf erosion markers used to train the ANN. The wavelengths are comprised between 120 and 200 Å.

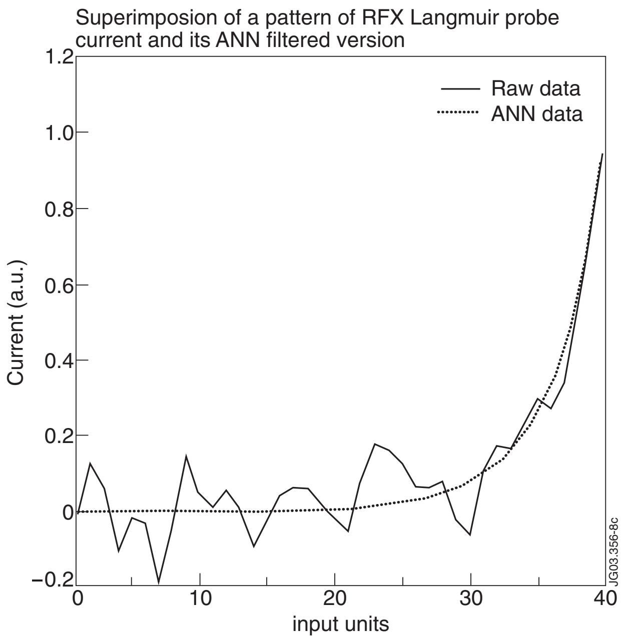

Figure 8: Example of a filtered version of an RFX probe current exponential curve, as computed by the ANN, superimposed to the related noisy input pattern.

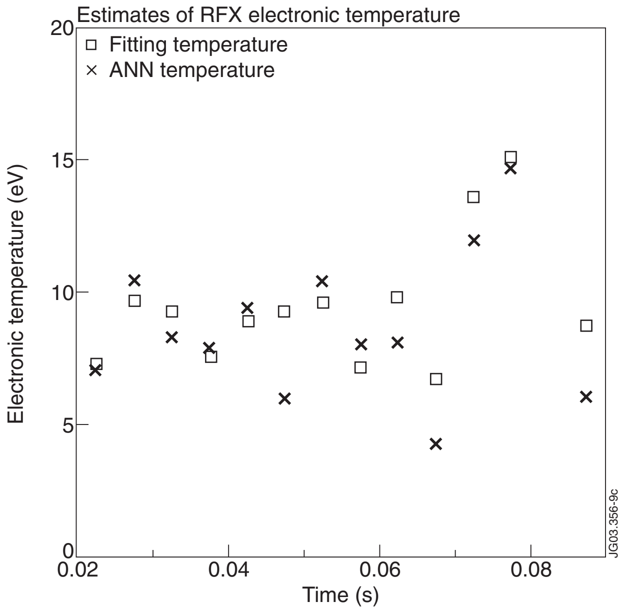

Figure 9: Comparison of estimates of RFX electronic temperature, during a pulse, as computed by the ANN and by the fitting procedure.